Linear-time Online Action Detection From 3D Skeletal Data Using Bags of Gesturelets

Moustafa Meshry, Mohamed E. Hussein and Marwan Torki

This paper is accepted for publication at the IEEE Winter Conference on Applications of Computer Vision, Lake Placid, NY, 2016

Copyright @ IEEE 2016

Linear-time Online Action Detection From 3D Skeletal Data Using Bags of Gesturelets

Moustafa Meshry¹ Mohamed E. Hussein^{1,2*} Marwan Torki¹

¹ Dept. of Computer and Systems Engineering, Alexandria University, Egypt

² Dept. of Computer Science and Engineering, Egypt-Japan University of Science and Technology

moustafa.meshry@alexu.edu.eg, mohamed.e.hussein@ejust.edu.eg, mtorki@alexu.edu.eg

Abstract

Sliding window is one direct way to extend a successful recognition system to handle the more challenging detection problem. While action recognition decides only whether or not an action is present in a pre-segmented video sequence, action detection identifies the time interval where the action occurred in an unsegmented video stream. Sliding window approaches can however be slow as they maximize a classifier score over all possible sub-intervals. Even though new schemes utilize dynamic programming to speed up the search for the optimal sub-interval, they require offline processing on the whole video sequence. In this paper, we propose a novel approach for online action detection based on 3D skeleton sequences extracted from depth data. It identifies the sub-interval with the maximum classifier score in linear time. Furthermore, it is suitable for real-time applications with low latency.

1. Introduction

Human action detection at real-time has become a topic of increasing interest due to its wide practical use. Applications like Human-machine interaction, surveillance and gaming, all require accurate and low-latency action detection. Action detection on raw videos is difficult because it is first needed to localize a person in a scene full of objects and clutter, then try to recognize the type of action being performed. On the other hand, the recent low-cost depth sensors, like Microsoft Kinect, provided a more convenient way for data capture. The 3D positions of body joints can be estimated from depth maps at low-latency and with acceptable accuracy. Filtering out background clutter, it is now more adequate to perform action detection based on skeleton data. Recently, skeleton-based approaches to

action recognition and detection have been widely adopted. While action recognition focuses on identifying the action label of pre-segmented video sequences, action detection tackles the more challenging problem of temporally localizing the action in an unsegmented stream of frames.

The main contribution of this paper is a novel approach for action detection from skeleton data, that we refer to as Efficient Linear Search (ELS). We show that a combination of simple components and specializing them towards skeleton-based action detection can achieve state-of-the-art results and overcome the limitations of similar approaches. The proposed approach is flexible: it can be used with a wide class of classifier functions and with different types of action local descriptors. As a byproduct contribution, we propose a simple skeleton-based local descriptor that, when used in a simple bag-of-features model, produces state-of-the-art results on different datasets. The proposed framework works online and is suitable for real-time applications. Moreover, it can be used for real-time video segmentation, since it specifies both the start and end frames of the action.

The rest of this paper is organized as follows: section 2 gives an overview about recent related work in the literature. We show the used action representation and our proposed descriptor in section 3. We, then, explain our Efficient Linear Search approach in section 4. Experimental evaluation is presented in 5. And finally, we conclude in 6.

2. Related work

Forming suitable skeletal-based descriptors for action recognition has been the focus of many recent research works [6, 11, 12, 14, 17, 20, 22, 23]. The objective is to facilitate the recognition task via a discriminative descriptor. Some of these descriptors capture both the pose of the skeleton and the kinematics at the same time on the frame level. For example, Nowozin $et\ al.\ [11]$ proposed a local descriptor that uses 35 angles between triplets of joints, $\Theta(t_0)$, along with angular velocity, $\delta\Theta(t_0)$, to encode joints' kinematics. Joints angles are a powerful cue to skeleton pose.

^{*}Mohamed E. Hussein is currently an Assistant Professor at Egypt-Japan University of Science and Technology, on leave from his position at Alexandria University.

Moreover, they are invariant to body translation and rotation. Later, Zanfir *et al.* [22] proposed the Moving Pose descriptor, which captures both the body pose at one frame, as well as the speed and acceleration of body joints within a short time window centered around the current frame.

Another class of descriptors is focused on computing a fixed length descriptor for the whole action sequence, like [6, 7, 15, 17]. Gowayyed *et al.* [6] used a 2D trajectory descriptor, called "Histogram of Oriented Displacements" (HOD), where each displacement in the trajectory casts a vote, weighted by its length, in a histogram of orientation angles. Vemulapalli *et al.* [15] modeled human actions as curves in a Lie group, since 3D rigid body motions are members of the special Euclidean group. Wang *et al.* [17] used the 3D joints positions to construct a descriptor of relative positions between joints. However, descriptors on the whole sequence suffer from much higher dimensionality over those that were designed for the frame level. This higher dimensionality led sometimes to the need for feature selection as done in [12, 14].

While most of the focus on skeletal data was about action recognition, fewer works focused on the online problem. The trade-off between latency and accuracy was addressed in recent works [4, 11, 14, 20, 22, 23]. In [11] the notion of action points was first introduced and the detection problem was cast as a classification problem for every overlapping 35-frames intervals. The same notion of action points was utilized in the work of [14], but they could handle different scales. Other works, such as [20, 22, 23] used the standard sliding window protocol for online action detection. Zhao et al. [23] proposed a feature extraction method, called "Structured Streaming Skeleton" (SSS), which constructs a feature vector for each frame using a dynamic matching approach. The SSS feature vectors are then used for detecting the start and end of actions. Zanfir et al. [22]used a modified kNN classifier to detect the start and end of actions. However, both [22, 23] cannot handle multi-scale actions, where the same action can be performed at different speeds.

3. Bag-of-gesturelets for action classification

The concept of local features first appeared in object detection in images [13]. The main idea is that each object has a set of discriminative local features that, if appeared together, signify the existence of the object. Same concept applies to actions. For a specific action, we can identify a set of key frames that best capture the discriminative poses of this action. However, skeleton poses alone cannot distinguish between some actions, e.g. standing up vs. sitting down, since other information like the direction and speed of motion play an important role in identifying the action. So, differential quantities that describe joints' kinematics must be included in an action's local features. We then define a *gesturelet* to be any general local feature that, for any

frame, captures both the skeleton pose and kinematic information of body joints at this point in time. In the following, we first introduce our action representation as a bag of gesturelets. Then, we explain our local features descriptor for representing gesturelets.

3.1. A bag-of-gesturelets representation

Based on extracted gesturelets from action sequences, we make use of a bag-of-gesturelets (BoG) representation of human actions. We first extract features at each frame. Resulting descriptors are then clustered to produce a K-entry codebook. We then represent any action sequence or sub-sequence by its cluster histogram, where the histogram counts how many local features from each cluster index have occurred. In order to relax the assignment of each gesturelet to its representative cluster in the codebook, we apply *soft binning*; letting each gesturelet cast a vote to its m nearest clusters. The vote will be weighted according to the distance between the gesturelet and the corresponding cluster, so that closer clusters get higher weight. Implementation details for soft binning are presented in section 5.2.

The BoG representation is necessary for our approach for action detection, as we show in section 4. However, as shown in section 5.3, it is also very effective for action recognition. This BoG representation is independent of the choice of the local descriptor used to represent a gesturelet. Possible descriptors that capture both pose information and joints kinematics are [11, 14, 20, 22].

3.2. Our local descriptor

The type of local descriptor has a direct impact on the recognition performance. We experimented with different descriptors, and as a byproduct contribution, we achieved best results with a proposed local descriptor that is a weighted concatenation of the angles descriptor [11] and a slight modification of the Moving Pose descriptor [22]¹. The angles descriptor uses 35 angles between triplets of joints, $\Theta(t_0)$, along with angular velocity, $\delta\Theta(t_0)$. On the other hand, the Moving Pose descriptor relies on joints positions, $P(t_0)$, relative to a reference joint, namely the hip center. And to capture kinematic information, it includes the first and second order derivatives; $\delta P(t_0)$ and $\delta^2 P(t_0)$. The final form of our descriptor is $[[P, \alpha \delta P, \beta \delta^2 P] \mid \psi[\Theta, \delta \Theta]],$ where α and β are parameters defined in [22], and ψ is a weighting parameter to the relative importance of the two concatenated descriptors. In our experiments in section 5, we show that using our simple descriptor and with basic dictionary learning, we can achieve state-of-the-art results over different datasets.

¹We modify the descriptor by rescaling the vector of concatenated joint positions to unit norm.

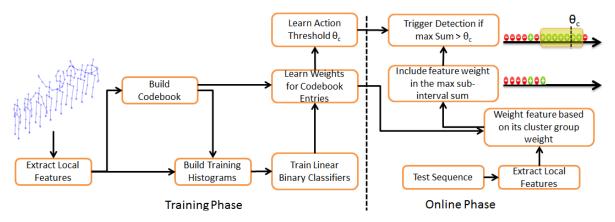


Figure 1: Efficient Linear Search Overview. The goal of the training phase is to learn weights for each features-cluster. At test time, each extracted feature will be weighted by its cluster weight, and incorporated in the search for the maximum sub-interval sum. If the sum at time t_i is above a learned threshold θ_c and starts to decrease, then a detection is triggered for action class c.

4. Efficient Linear Search (ELS)

In this section, we first explain our approach on offline action detection. Then, we show how it can be easily extended to work for online detection as well. Figure 1 gives an overview of the approach.

Although many successful skeleton-based action recognition systems exist, most of them haven't been extended to action detection. Sliding window approaches can be used for this task, evaluating the classifier function over all candidate sub-intervals. So, for a video sequence S, it will identify the sub-interval, $s_{action} = [t_{st}, t_{end}]$, for which the classifier function produces the maximum score.

$$s_{action} = argmax_{s \subset S} f(s) \tag{1}$$

This identifies only one occurrence of the target action in the sequence. If multiple occurrences are to be found, then we can simply remove sub-intervals corresponding to previously identified actions, and repeat the search for the next s_{max} . However, for a sequence of N frames, we have $O(N^2)$ candidate sub-intervals, which incurs significant computational complexity. Thanks to Lampert et al. [8], an efficient branch-and-bound method was proposed to search for the optimal bounding box of an object in an image. A limitation to branch-and-bound approaches is that they typically work offline, requiring the whole search space beforehand, as in [8, 21]. In [21], Yuan et al. proposed a direct extension of [8] on action detection from RGB videos. They used a bag-of-features model based on spatio-temporal features, and proposed an offline action detection system. Another limitation to [8, 21] is that, optimizing equation 1 may not always produce the desired behavior for a detection procedure since the optimal interval may contain multiple consecutive instances of an action. This problem is less likely to happen in the case of 2D images, for which the original branch-and-bound approach was first introduced [8].

In the following, we present a specialization of the branch-and-bound approach to the case of skeleton-based action detection. This turns out to be easily cast as one of the well-known dynamic programming problems that can be solved in linear time. Next, we show that a greedy approximation can effectively address the offline limitation of the branch-and-bound approach, as well as the problem of combining consecutive actions. We assume two conditions: (1) a bag-of-gesturelets representation of action sequences, and (2) a linear binary classifier with good recognition accuracy trained for a specific target action. While the linear classifier constraint is not necessary, as we later show, we will use this assumption for simplicity of explanation.

4.1. Offline action detection

For any linear classifier, the corresponding scoring and decision functions take the form of:

$$f(S) = w^T x + w_0, \quad y(S) = \begin{cases} 1 & \text{if } f(S) > 0\\ 0 & \text{otherwise} \end{cases}$$
 (2)

where S is a test sequence or sub-sequence, x is the feature vector of S, w is the weight vector learned by the classifier, and w_0 is a constant bias. With the linearity of the dot product, $w^T x$, and the fact that x is a histogram that counts the occurrence of each cluster index, the scoring function 2 can be rewritten as:

$$f(S) = w_0 + \sum_{j=1}^{n} w_{c_j}$$
 (3)

where, c_j is the cluster index to which gesturelet x_j belongs, and n is the total number of gesturelets extracted from sequence S. We can then evaluate the classifier function over

²For simplicity of presentation, this formulation does not consider soft binning in histogram construction. Including soft binning is straight forward though.

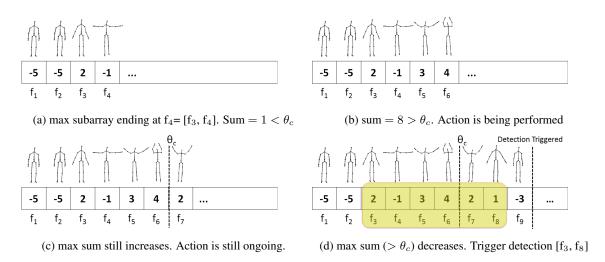


Figure 2: Example of online detection. We assume the action threshold $\theta_c = 7$. Detected interval is $[f_3, f_8]$.

any sub-sequence $s\subseteq S$ by summing the weights, w_{c_j} , of gesturelets x_j that only belong to the sub-sequence s. Since we want to identify the sub-sequence $s\subseteq S$ that maximizes equation (3), we can safely drop the bias term, w_0 .

The offline detection procedure will then be as follows: construct an empty 1D score array, with length equal to the number of frames. This array will represent the perpoint contribution of all extracted features from test sequence S. For each feature x_i , identify its cluster index c_j , then add up its weight, w_{c_j} , to the frame index in the score array. Finding the start and end frames of the action, $s_{action} = [t_{st}, t_{end}]$, that satisfy equation 1 can now be mapped to finding the maximum subarray sum in the score array. Thanks to Kadane's algorithm [1], this can be done in linear time in the number of frames, using dynamic programming. If $f(s_{max}) \ge \theta_c$, where θ_c is a learned threshold for action class c, then we specify that action c has occurred, and we return the start and end frames of the sub-sequence s_{max} . To learn the action threshold for each action class, we compute the score of all training sequences, and search for the score threshold, θ_c , that minimizes the binary classification error on the training data for class c.

To detect different action classes, we will construct a one-versus-all binary classification model for each action class. What differs from one action class to another is the classification model weights assigned to each entry in the codebook, along with the learned threshold θ_c . The detection procedure for each of the classes can then be run concurrently on the action sequence with different per-point feature weights for each action class.

It is noted that, while the linearity of the classifier is a sufficient condition, it is not necessary. Any type of classification method that can output a classification score at the frame level can be used with our approach, since we later learn the score threshold, θ_c , explicitly. This gives flexibil-

ity to our approach with a wider range of classifiers.

4.2. Online action detection

In this section we extend our approach to handle online action detection. To find the maximum subarray sum, Kadane's algorithm scans through the array. At each position (frame), it identifies the subinterval ending at this position with the maximum sum. Since we only trigger the action if the maximum sum is larger than a learned threshold θ_c , then at any time t_i , if the maximum sum ending at frame i exceeds θ_c , then we know that action c is being performed, and our task, then, is to find at which frame the action will end. We expect that after the action ends, we will encounter a contiguous sequence of frames with negative scores. So, for the next frames, as long as the maximum sum grows, the action is still on-going. Once the subarray sum starts to decrease, we can assume that the action has ended. There will be a compromise between latency and confidence. If we specify the end of action at the first negative point score, this will be very sensitive to noise but it will achieve low latency. If we wait till we encounter two consecutive points with negative scores, then this will achieve higher confidence at the expense of increased latency, and so on. In our experiments, we found that triggering the action at the first frame with negative score, after exceeding the threshold θ_c , causes a slight decrease of accuracy, while achieving very low latency. Figure 2 shows an example of how online detection works.

As we hinted before, a problem to the offline detection procedure is that it may combine consecutive repetitions of the same action in one detection. If an action is repeated twice, with a short pause between them, we expect that each repetition will yield a high positive response, while the pause between them will have a negative response, but not as high. So, optimizing equation 1 would combine the two

repetitions together. To separate the two repetitions, the separating negative score must be high. This problem is solved in online detection with the greedy approach to terminating the action, which only requires consecutive frames with negative scores, without further restrictions on their weight. Section 5.5 compares offline and online detection to highlight this offline detection limitation.

Detecting multiple classes in the online case is similar to the offline case, except that if one action class is detected at time t_i , then the detection procedure for all other classes is reset, and the search for a new detection starts from time t_{i+1} .

5. Experimental results

In this section, we first describe the two datasets used in our experiments. We then expand on our implementation details. Then, we compare the performance of our approach to the state of the art on both datasets. We start with the performance on the more classical action recognition task, then, we move to online action detection. Next, we compare offline and online detections. After that, we show how the performance of our approach is affected by changing its main parameters. Finally, we demonstrate its real-time performance.

5.1. Datasets

MSRC-12: The Microsoft Research Cambridge-12 dataset [5] is a large dataset designed for action detection. It contains more than 700,000 frames in 594 unsegmented sequences, encompassing 6,244 gesture instances, recorded for 30 subjects performing 12 different gestures. The samples consist of the 3D positions of 20 joints of the body skeleton captured using the Microsoft Kinect sensor at 30 fps. The MSRC-12 dataset is annotated using the notion of an Action Point, which is a pose within the gesture that clearly identifies its completion.

MSR-Action3D: MSR-Action3D dataset [9] is a standard dataset for action recognition. It consists of 557 pre-segmented sequences, with more than 20,000 frames. There are 10 subjects performing 20 different action gestures. Similar to MSRC-12, the 3D positions of 20 joints are captured using the Microsoft Kinect sensor.

5.2. Implementation details

For the linear classifier through our experiments, we use an SVM [2] with a linear kernel. The local descriptor has three parameters, α , β , and ψ . While α , β are inherited from the Moving Pose descriptor [22], we introduced ψ to weight the relative importance of the two concatenated descriptors. Coarse-grain values for the parameters were learned from the training set, using different combinations of the 3 parameters in a brute-force manner. Trial-and-error was

then used to fine-tune the parameters' values. For MSR-Action3D, we split the training set, persons $\{1,3,5,7,9\}$, into training and validation sets, using 40% of the training data (persons 7 and 9) as a validation set. Learned parameters ($\alpha=1,\beta=1,\psi=1.7$) were then fixed for all test experiments on MSR-Action3D. For MSRC-12, the parameters were learned over one modality (20% of the dataset), namely the video modality. Learned values ($\alpha=0.375,\beta=0.3,\psi=0.2$) were then used in test experiments over all modalities. For soft-binning, we set the number of neighbors, m, to 3. The vote to the i^{th} nearest cluster is weighted by 1/i. A control experiment for choosing m is shown in section 5.6.

The unsegmented sequences for the MSRC-12 dataset contain pauses between consecutive action instances, in which the actor often stands still in a neutral pose. Such a neutral pose also occurs at the beginning and ending of most action instances. Therefore, the neutral pose does not discriminate between different action classes, and hence, the classifier may be tempted to give it a neutral weight, possibly positive in sign. This would cause a problem for our detection procedure, which relies on having negative scores right before and after an action instance. To overcome this problem, we add hard negatives to the negative training samples used to train our binary classifiers. Each of these hard negatives consists of one positive instance followed by a pause between two consecutive instances. In this way, the classifier is forced to give strong negative scores to the neutral poses in order to discriminate between those hard negatives and the positive samples, which solves the issue for the detection procedure. A similar problem occurs in the detection on unsegmented sequences from the MSR-Action3D dataset. Actions start and end with neutral poses, which could again cause issues in localizing the beginning and ending of action instances. In this case, we include concatenations of two action instances as hard negatives in the binary classifier training.

A weighted moving-average on the frames scores was applied, where the anchor frame had weight equal to number of its neighbors. For MSRC-12, we used a window of 5 frames, anchored at the middle frame (just as in the local descriptor). For MSR-Action, we used a window of 3 frames, since MSR-Action3D sequences are much smaller than those of MSRC-12.

5.3. Action recognition

First, to demonstrate the discriminative power of the BoG representation 3.1, we report recognition results on both MSR-Action3D and MSRC-12 datasets. For MSR-Action3D, we follow the same experimental setup as [9]; dividing the dataset into 3 action sets and training with sequences performed by subjects $\{1,3,5,7,9\}$. Average accuracy over the 3 action sets is then reported. We report

	Fothergill et al.[5]	Sharaf et al.[14]	ELS
Video - Text	0.679 ± 0.035	0.713 ± 0.105	0.790 ± 0.133
Image - Text	0.563 ± 0.045	0.656 ± 0.122	0.711 ± 0.228
Text	0.479 ± 0.104	0.521 ± 0.072	0.622 ± 0.246
Video	0.627 ± 0.052	0.635 ± 0.075	0.726 ± 0.225
Image	0.549 ± 0.102	0.596 ± 0.103	0.670 ± 0.254
Overall	0.579	0.624	0.704

Table 3: Detection experiment for MSRC-12 dataset at $\triangle=333ms$ latency. Mean F-score and its standard deviation is reported for each instruction modality.

Method	Accuracy
Eigenjoints [19]	82.3%
Random Occupy Pattern [16]	86.2%
Actionlets Ensemble [17]	88.2%
Covariance Descriptor (Cov3DJ) [7]	90.5%
Angles Covariance Descriptor [14]	91.1%
Histogram of Oriented	91.26%
Displacements (HOD) [6]	
Fusing Spatiotemporal Features [24]	94.3%
Group Sparsity and Geometry Constrained	97.27 %
Dictionary Learning (DL-GSGC) [10]	
Our Approach	$96.05 \pm 0.39\%$

Table 1: Comparative recognition results on MSR-Action3D.

Method	Accuracy
Cov3DJ Descriptor [7]	94.48%
Our Approach	96.83%

Table 2: Recognition results on MSRC-12 dataset.

the average classification rate and its standard deviation over 5 runs with 5 different codebooks. Table 1 compares our results to state-of-the-art approaches. As results show, the only approach that outperforms ours is DL-GSGC [10], where a dictionary learning algorithm is proposed for sparse coding. DL-GSGC adds group sparsity and geometric constraints to reconstruct feature points with minimal error. On the other hand, we achieve very competitive results using basic dictionary learning with simple k-means clustering.

We also report classification results on MSRC-12 dataset. Since this dataset is originally unsegmented and labeled with action points only, we use the annotation and experimental setup of [7] and compare our results to theirs in table 2. It is noted that, in [7], the covariance descriptor is used as a global descriptor constructed for the entire action sequence, while we use a local features approach to represent the action sequence. This signifies the power of

using local pose information in addition to joints kinematics information, instead of encoding global kinematic information only as in [7].

5.4. Online action detection

5.4.1 Action detection on MSRC-12 dataset

As mentioned before, MSRC-12 is annotated with action points. So, most approaches experimenting on MSRC-12 (e.g. [5, 14]) convert the problem of real time action detection into classifying each frame as an action point or not, in real time. A positive detection is regarded when the gesture occurrence is detected within a short time window from the ground truth action point. Thanks to [7], they provided manual annotation for the start and end frames of each gesture instance, which is needed to train classifiers for accurate action segmentation. To be able to compare our results to [5, 14], we regard the gesture occurrence to begin at the start frame as in the annotation of [7], and ends at the action point annotation. Our method, then, should trigger the occurrence of a gesture at its ground truth action point as in [5, 14]. Within each modality, we measure the precision and recall of each action class across all 10 folds. We then report the average F-score.

We use two different precision-recall experimental protocols. First, a positive detection is counted if the detection is triggered within 10 frames from the action point, this is a latency of 0.333 seconds as in [5, 14]. Table 3 compares results of ELS against state-of-the-art results on MSRC-12.

The is noted that we don't compare with [23], as they use a different protocol for F-score calculation.

Second, we use the standard precision-recall experimental protocol used in object detection in images, which is an overlap threshold of 0.2, as in [3, 22]. This is to demonstrate the power of our approach for real-time segmentation of the temporal sequence, identifying the start and end of a gesture online and in real-time. Since we are the first to report overlap results on MSRC-12, we obtained the state-of-theart code of Sharaf *et al.*[14] and reported its overlap results.

³Before the camera ready version, we found [18] which reports better results on MSRC-12.

	Sharaf et al. [14]	ELS	ELS
	at 0.2 overlap	at 0.2 overlap	at 0.5 overlap
Video - Text	0.684 ± 0.074	0.921 ± 0.126	0.866 ± 0.146
Image - Text	0.687 ± 0.099	0.894 ± 0.085	0.806 ± 0.099
Text	0.558 ± 0.092	0.788 ± 0.139	0.710 ± 0.158
Video	0.669 ± 0.082	0.895 ± 0.068	0.821 ± 0.093
Image	0.598 ± 0.082	0.858 ± 0.086	0.734 ± 0.130
Overall	0.639	0.871	0.787

Table 4: Overlap detection experiment for MSRC-12 dataset at 0.2 and 0.5 overlap ratios. Mean F-score and its standard deviation is reported for each instruction modality.

We compare results in table 4. The results show that our approach significantly outperforms the state-of-the-art results in the overlap experiment. Our results for a 0.5 overlap ratio are still even better than Sharaf *et al.* with a 0.2 overlap ratio. This emphasizes the power of our approach for real-time action segmentation. It is noted that although [14] uses a multi-scale approach, but it operates on the level of the whole action sequence. On the other hand, the granularity of our approach is a single frame with a small temporal window of 2 frames on each side. Such finer granularity gives higher flexibility when identifying the start and end of actions of different lengths and/or speed.

5.4.2 Action detection on MSR-Action3D dataset

To further test our approach on another dataset, we conduct the same experiment of [22] for online action detection on MSR-Action3D. Since MSR-Action3D is designed for action recognition, where action sequences are presegmented, [22] concatenates all test sequences in a random order to create one long unsegmented test sequence for action detection. To be able to compare our results to [22], we train with persons $\{1, 2, 3, 4, 5\}$ and test with the rest. We also repeat this experiment 100 times with different random concatenation ordering as done in [22], and compare our results in table 5. As results show, we are on the bar with state-of-the-art results on this dataset. It is, however, noted that a limitation to [22] is using k-NN search on all training frames. This works well for small datasets, like MSR-Action3D. However, for large datasets, k-NN will potentially incur significant space and time requirements. On the other hand, the complexity of our approach is primarily affected by the codebook size, which is significantly smaller than the number of frames in the training data.

5.5. Offline vs online detection

Table 6 compares offline and online detection results on both MSRC-12 and MSR-Action3D datasets. It reports the detection F-score for a 0.2 overlap ratio. The results highlight the limitations of offline detection and how the online

Method	Detection mean AP
The Moving Pose[22]	0.890 ± 0.002
ELS	0.902 ± 0.007

Table 5: Detection experiment for MSR-Action3D at a 0.2 overlap ratio.

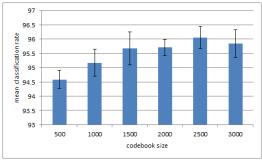
detection overcomes them, as illustrated in 4.2. Since the unsegmented sequences in MSRC-12 are mainly repeated performances of the same action class, the offline detection procedure first concatenated all repetitions in one long detection. Although hard negatives 5.2 partially solved this problem, but still around 85% of the gestures that failed to be detected, were missed due to concatenation to subsequent actions. For MSR-Action3D, around 64% of actions that failed to be detected were missed due to partial or complete concatenation to subsequent actions. For example, in the synthesized unsegmented test sequence, there were 14 occurrences where the same action was repeated twice. While the online detection successfully separated and detected the two repeated actions in 13 out of 14 occurrences, the offline detection failed to separate the two repeated actions in all 14 occurrences.

Dataset	Offline F-score	Online F-score
MSRC-12	0.524	0.871
MSR-Action3D	0.794	0.930

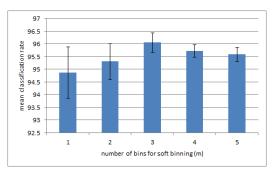
Table 6: Offline and online detection F-score, for a 0.2 overlap ratio

5.6. Sensitivity analysis

In this section we show the sensitivity of our framework's performance to changing different parameters. We conduct these experiments on the MSR-Action3D dataset since it is of reasonable size, which allows extensive experimentation. Without loss of generality, we conduct these experiments on the more basic action recognition task. Since



(a) Recognition results vs codebook size for MSR-Action3D



(b) Recognition results vs number of neighbors, m, for soft-binning

Figure 3: Control Experiments

our results depend on the constructed codebook, whose construction involves randomness, we repeat each experiment 5 times using 5 different codebooks and report the mean result and its standard deviation.

The first parameter is the choice of codebook size, K. The suitable codebook size is expected to be proportional to the target dataset size and the number of gesture classes in it. Figure 3a shows recognition results on MSR-Action3D with different codebook sizes. The results show that our framework is not sensitive to the choice of codebook size. It works well even in the case of small codebooks. Also, the small standard deviation means that the clustering randomness in codebook construction is of minor effect. This indicates both the robustness of our approach, and the discriminative power of our local descriptor.

Next, we show the effect of using soft binning 3.1 with different choices of m, where m is the number of neighbors for which each feature casts a weighted vote. For this experiment, we fix the codebook size to 2500, and plot recognition result vs. different settings of m in figure 3b. Although recognition accuracy improves in the case of using soft binning, the more important effect is evident in how the standard deviation significantly reduces with an increased value of m. This is because, with soft binning, it is less likely to miss voting for the correct representative cluster, unlike the hard assignment to one cluster only.

Last, we show the effect of using different local descriptors with our approach, in table 7. We achieve best results using our proposed descriptor 3.2.

5.7. Real-time operation

The goal of our framework is not only to perform online action detection, but also to do this in real-time. There are 3 main factors affecting the running time of our approach: 1) Size of the codebook; 2) Size of the local descriptor. 3) Number of neighbors, m, to vote for, in soft binning. For this experiment, we used a large codebook of size 3000. The dimensionality of our descriptor is 250, and we used m=3.

Used descriptor	Accuracy
Angles Covariance [14]	83.93%
Angles Descriptor [11]	86.25%
The Moving Pose [22]	94.01%
Our proposed descriptor	96.05%

Table 7: Effect of using different features in our approach on MSR-Action3D recognition

The average running-time per frame of our MATLAB implementation 4 was measured to be 10.7ms. So, our framework can process approximately 93 frames per second. The running-time was measured on a machine with 2.2 GHz Intel quad-core Core-i7 processor and 12 GB RAM.

6. Conclusion

We have proposed both a simple skeleton-based descriptor and a novel approach for action detection. The proposed approach maximizes a binary classifier score over all possible sub-sequences, typically in linear time. It can be used in conjunction with a large class of classifiers and with any local descriptor. Our proposed approach works online and at real-time with low latency. It detects a gesture by specifying its start and end frames in an unsegmented video sequence, which makes it suitable for real-time video temporal segmentation. While the proposed method relies on simple components, we showed that a specialization for skeleton-based action detection can be established which, not only outperforms the state-of-the-art, but also overcomes the limitations of similar approaches.

7. Acknowledgement

The authors would like to thank SmartCI Research Center for supporting this research.

⁴Matlab source code is available on the authors' webpages.

References

- [1] J. Bentley. Programming pearls: algorithm design techniques. *Communications of the ACM*, 27(9):865–873, 1984.
- [2] C.-C. Chang and C.-J. Lin. LIBSVM: A library for support vector machines. ACM Transactions on Intelligent Systems and Technology, 2:27:1-27:27, 2011. Software available at http://www.csie.ntu.edu.tw/ ~cjlin/libsvm.
- [3] O. Duchenne, I. Laptev, J. Sivic, F. Bach, and J. Ponce. Automatic annotation of human actions in video. In *Computer Vision*, 2009 IEEE 12th International Conference on, pages 1491–1498. IEEE, 2009.
- [4] C. Ellis, S. Z. Masood, M. F. Tappen, J. J. Laviola Jr, and R. Sukthankar. Exploring the trade-off between accuracy and observational latency in action recognition. *International Journal of Computer Vision*, 101(3):420–436, 2013.
- [5] S. Fothergill, H. Mentis, P. Kohli, and S. Nowozin. Instructing people for training gestural interactive systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, pages 1737–1746. ACM, 2012.
- [6] M. A. Gowayyed, M. Torki, M. E. Hussein, and M. El-Saban. Histogram of oriented displacements (hod): describing trajectories of human joints for action recognition. In *Proceedings of the Twenty-Third international joint conference on Artificial Intelligence*, pages 1351–1357. AAAI Press, 2013.
- [7] M. E. Hussein, M. Torki, M. A. Gowayyed, and M. El-Saban. Human action recognition using a temporal hierarchy of covariance descriptors on 3d joint locations. In *Proceedings of* the Twenty-Third international joint conference on Artificial Intelligence, pages 2466–2472. AAAI Press, 2013.
- [8] C. H. Lampert, M. B. Blaschko, and T. Hofmann. Beyond sliding windows: Object localization by efficient subwindow search. In *Computer Vision and Pattern Recognition*, 2008. CVPR 2008. IEEE Conference on, pages 1–8. IEEE, 2008.
- [9] W. Li, Z. Zhang, and Z. Liu. Action recognition based on a bag of 3d points. In *Computer Vision and Pattern Recog*nition Workshops (CVPRW), 2010 IEEE Computer Society Conference on, pages 9–14. IEEE, 2010.
- [10] J. Luo, W. Wang, and H. Qi. Group sparsity and geometry constrained dictionary learning for action recognition from depth maps. In *Computer Vision (ICCV)*, 2013 IEEE International Conference on, pages 1809–1816. IEEE, 2013.
- [11] S. Nowozin and J. Shotton. Action points: A representation for low-latency online human action recognition. *Microsoft Research Cambridge, Tech. Rep. MSR-TR-2012-68*, 2012.
- [12] F. Offi, R. Chaudhry, G. Kurillo, R. Vidal, and R. Bajcsy. Sequence of the most informative joints (smij): A new representation for human skeletal action recognition. *Journal of Visual Communication and Image Representation*, 25(1):24–38, 2014.
- [13] C. Schmid and R. Mohr. Local grayvalue invariants for image retrieval. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 19(5):530–534, 1997.
- [14] A. Sharaf, M. Torki, M. E. Hussein, and M. El-Saban. Real-time multi-scale action detection from 3d skeleton data. In *Applications of Computer Vision (WACV)*, 2015 IEEE Winter Conference on, pages 998–1005. IEEE, 2015.

- [15] R. Vemulapalli, F. Arrate, and R. Chellappa. Human action recognition by representing 3d skeletons as points in a lie group. In *Computer Vision and Pattern Recognition (CVPR)*, 2014 IEEE Conference on, pages 588–595. IEEE, 2014.
- [16] J. Wang, Z. Liu, J. Chorowski, Z. Chen, and Y. Wu. Robust 3d action recognition with random occupancy patterns. In *Computer Vision–ECCV 2012*, pages 872–885. Springer, 2012.
- [17] J. Wang, Z. Liu, Y. Wu, and J. Yuan. Mining actionlet ensemble for action recognition with depth cameras. In *Computer Vision and Pattern Recognition (CVPR)*, 2012 IEEE Conference on, pages 1290–1297. IEEE, 2012.
- [18] D. Wu and L. Shao. Leveraging hierarchical parametric networks for skeletal joints based action segmentation and recognition. In *Computer Vision and Pattern Recognition* (CVPR), 2014 IEEE Conference on, pages 724–731. IEEE, 2014.
- [19] X. Yang and Y. Tian. Eigenjoints-based action recognition using naive-bayes-nearest-neighbor. In Computer Vision and Pattern Recognition Workshops (CVPRW), 2012 IEEE Computer Society Conference on, pages 14–19. IEEE, 2012.
- [20] G. Yu, Z. Liu, and J. Yuan. Discriminative orderlet mining for real-time recognition of human-object interaction. In *Computer Vision–ACCV 2014*, pages 50–65. Springer, 2015.
- [21] J. Yuan, Z. Liu, and Y. Wu. Discriminative video pattern search for efficient action detection. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 33(9):1728–1743, 2011.
- [22] M. Zanfir, M. Leordeanu, and C. Sminchisescu. The moving pose: An efficient 3d kinematics descriptor for low-latency action recognition and detection. In *Computer Vision (ICCV)*, 2013 IEEE International Conference on, pages 2752–2759. IEEE, 2013.
- [23] X. Zhao, X. Li, C. Pang, Q. Z. Sheng, S. Wang, and M. Ye. Structured streaming skeleton—a new feature for online human gesture recognition. ACM Transactions on Multimedia Computing, Communications, and Applications (TOMM), 11(1s):22, 2014.
- [24] Y. Zhu, W. Chen, and G. Guo. Fusing spatiotemporal features and joints for 3d action recognition. In *Computer Vision and Pattern Recognition Workshops (CVPRW)*, 2013 IEEE Conference on, pages 486–491. IEEE, 2013.